Applying Cognitive Methodology in Designing On-Line Auto-Tuning Robust PID Controller for the Real Heating System

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ABSTRACT

A novel design and implementation of a cognitive methodology for the on-line auto-tuning robust PID controller in a real heating system is presented in this paper. The aim of the proposed work is to construct a cognitive control methodology that gives optimal control signal to the heating system, which achieve the following objectives: fast and precise search efficiency in finding the on-line optimal PID controller parameters in order to find the optimal output temperature response for the heating system. The cognitive methodology (CM) consists of three engines: breeding engine based Routh-Hurwitz criterion stability, search engine based particle swarm optimization (PSO) and aggregation knowledge engine based cultural algorithm (CA). Matlab simulation package is used to carry out the proposed methodology that finds and tunes the optimal values of the robust PID parameters on-line. In real-time, the LabVIEW package is guided to design the on-line robust PID controller for the heating system. Numerical simulations and experimental results are compared with each other and showed the effectiveness of the proposed control methodology in terms of fast and smooth dynamic response for the heating system, especially when the control methodology considers the external disturbance attenuation problem.

Key words: robust pid controller, cognitive, cultural algorithm, particle swarm optimization, heating system, matlab, labview.

تطبيق المنـهج الإدراكي في تصميم مسيطر تنـاسبي تكاملي تفاضلي متين بتنـغيم تلقائي بشكل حي متصل لنظام حراري حقيقي

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الخلاصة

في هذا البحث, تم تصميم وتنفيذ منهج إدراكي جديد مبتكر لمسيطر تناسبي تكاملي تفاضلي متين بتنغيم تلقائي وبشكل حي متصل لمنظومة حرارية حقيقية. أن الهدف من هذا العمل المقترح هو بناء منهجية السيطرة المدركة والتي تعطي أمثل أشارة سيطرة لنظام الحراري والتي حققت الغايات التالية: كفاءة عالية من حيث السرعة ودقة البحث لإيجاد امثل قيم لعناصر المسيطر وبشكل حي متصل والتي تؤدي لإيجاد أفضل استجابة حرارية للنظام. أن منهج الإدراكي المقترح يتألف من ثلاث محركات: محرك النسل

وأساسه معيارية راوث هيروتز الأستقرارية, ومحرك البحث وأساسه حشد الجسيمات الأمثلية, ومحرك المعرفة المتجمعة وأساسها الخوارزمية الحضارية. لقد تم استخدام حقيبة الماتلاب البرمجية للمحاكاة كأداة لتنفيذ المنهج المقترح لإيجاد وتنغيم القيم الأمثلية للمسيطر التناسبي التكاملي التفاضلي المتين وبشكل حي متصل.
في الزمن الحقيقي تم استخدام حقيبة اللاب فيو البرمجية لتصميم المسيطر التناسبي التكاملي التفاضلي المتين وبشكل حي متصل لنظام الحراري. المحاكاة العددية و النتائج التجريبية قورنت مع بعضها البعض لبيان فعالية المنهج السيطرة المقترح من حيث السرعة والاستجابة الديناميكية الناعمة لنظام الحراري, خصوصا عندما اخذ بنظر الاعتبار مشكلة التضعيف للضوضاء الخارجية.

الكلمات الرئيسية:المسيطر التناسبي التكاملي التفاضلي المتين, الإدراك, الخوارزمية الحضارية, حشد الجسيمات الامثلية, منظومة حرارية, ماتلاب, لاب فيو.

1. INTRODUCTION

Over the past decade, more than 90% of industrial controllers are still implemented based on PID control algorithms as no other controller matches the simplicity, effectiveness, robustness, clear functionality and ease of implementation**, Zhao, et al., 2011.** Several approaches have been used for tuning the parameters of PID controllers such as Ziegler-Nichols method**, Duarte,** and **Jose, 2006.**
In last years, time domain performance, frequency domain performance and robust performance criterion have been used in designing PID controllers where the output of PID controllers (proportional - integral - derivative) are a linear combination of its input i.e. the proportion of the input, the integral of input and the derivative of the input**, Hagglund,** and **Astrom, 1996**.
However, PID controller is sensitive to plant parameter variations and the controller gains must be carefully selected for a desired response, thus the motivation for this work is the robustness which is an important criterion in controller design because most of the real systems are vulnerable to external disturbance, measurement noise and model uncertainty. While many industrial plants are often burdened with problems such as high order, time delays, and nonlinearities; therefore, it has been quite difficult to tune properly the gains of PID controllers. So there are many algorithms to tune the parameters of the PID controller in order to avoid these problems in the prosperities of systems: The comparison of various intelligent techniques used for temperature control of water bath system that consists of different control schemes namely PID, PID using Genetic Algorithms (GA-PID), Fuzzy Logic Control, Neural Network, Adaptive Neuro-Fuzzy Inference System (ANFIS), and GA-ANFIS have been proposed in **Saini,** and **Rani, 2012**.
In addition to that, design and implementation of a temperature control system of the thermal analyzer by combining fuzzy and PID control methods and accomplishing a comparative experiment of conventional PID with fuzzy self-tuning PID control method was explained in **Dong, et al., 2009.** In **Wei, 2010,** was explained the algorithm that it improves the performance of the temperature control system based on fuzzy self-tuning PID. Also it investigated the applicability of Model Predictive Control (MPC) strategies to heating processes as proposed in**, Sbarciog, et al., 2008,** and used the nonlinear extended prediction self-adaptive control algorithm for the heated tank temperature.
The fundamental essence of the contribution of this work is to overcome the building of robust controller that has high order than that of the system where the controller is not easy to implement for this system in practical engineering application. This difficulty can be solved by the proposed algorithm that built a robust PID controller through applying the cognitive control methodology based CA and PSO technique, the proposed algorithm works as on-line auto-tuning for the PID

controller parameters on the real-time without time consuming as well as no requiring for tedious efforts.

In this paper, experimental investigation is carried out for the appropriate on-line auto-tuning parameters of the robust PID controller that controls the temperature of heating system using cognitive methodology to obtain the best temperature response achieved in real-time based on LabVIEW package.

The remainder of this paper is organized as follows: section two, describes the mathematic model of the heating system. In section three, the proposed cognitive control methodology for robust PID controller is explained. The Matlab simulation results of the proposed control algorithm are presented in section four. Hardware design and real-time results based on LabVIEW package are presented in section five and finally the conclusions are drawn in section six.

2. HEATING SYSTEM MODEL

The heating system model can be derived using the linear heat balance dynamic equation as follows, **Ogata, 2003**:

Heat input – Heat output = Heat accumulation

$$Q_i(t) - Q_{loss}(t) = Q_{Acc}(t) \tag{1}$$

Unsteady equation is:

$$Q_i(t) - hA(T(t) - T_{air}(t)) = Mcp\frac{dT(t)}{dt} \tag{2}$$

Steady equation at t=0 is

$$Q_i(0) - hA(T(0) - T_{air}(0)) = 0 \tag{3}$$

The difference between the Eqs. (2 and 3) becomes Eq. (4).

$$Q_i(t) - hAT(t) = Mcp\frac{dT(t)}{dt} \tag{4}$$

By taking Laplace Transformation for Eq. (4) in order to find the T.F. for the heating system as follows:

$$Q_i(s) - hAT(s) = McpST(s) \tag{5}$$

$$\frac{T(s)}{Q_i(s)} = \frac{1/hA}{Mcp/hAS + 1} \tag{6}$$

$$\frac{T(s)}{Q_i(s)} = \frac{K}{\tau S + 1} \tag{7}$$

where $K = 1/hA$ and $\tau = Mcp/hA$.

The real parameters implemented in the design of heating system are shown in **Table.1**.
After applying the real parameters of the heating system as in **Table 1.** in the T.F. Eq. (7), the model equation for the heating system will be as Eq. (8):

$$\frac{T(s)}{Q_i(s)} = \frac{1.21}{10.2S+1} \tag{8}$$

3. ROBUT PID CONTROLLER DESIGN

PID control is widely applied in industrial practice because of its simple structure that consists of three terms: proportional, integral and derivative where the standard form of a PID controller is given in the s-domain as Eq. (9), **Zhong, 2006**.

$$Gc(s) = P + I + D = K_p + \frac{K_i}{s} + K_d s \tag{9}$$

where K_p, K_i and K_d are called the proportional gain, the integral gain and the derivative gain respectively.
The PID controller is very important because it is necessary to stabilize the tracking error of the heating system temperature when the output temperature drifts from the desired temperature.
After understanding the profound theoretical fundamental for the PID parameters tuning algorithms and employing these algorithms in designing a robust PID controller especially for system model which has uncertain parameters such as T_{air} which causes the heat loss disturbances that effect on the temperature output of the real system
A novel cognitive control methodology is proposed to find and tune on-line the PID control parameters in order to get a good evaluation of the performance rejection of the heat loss disturbance and uncertain parameter for the real system then to obtain the optimal and robust PID control action.
Thus, the proposed cognitive control methodology has the characteristics of high control ability, strong adaptability, good dynamic characteristic and robustness.
The proposed structure of the on-line auto-tuning robust PID controller of the heating system can be given in the form of block diagram, as shown in **Fig. 1**.

3.1 Cognitive Control Methodology

Cognitive control methodologies have been proven to be a source of inspiration and guidance to overcome current limitations in the controller for complex and adaptive systems by aggregation knowledge and to structure this knowledge autonomously**, Al-Araji, 2012.**
The proposed cognitive control methodology consists of three engines: Aggregation Knowledge Engine, Search Engine and Breeding Engine.
The aggregation knowledge engine based on cultural algorithm (CA) has been developed by modeling how human culture work. Culture is viewed as a vehicle for storing relevant information gathered since the start of the culture, and is available to all the subsequent generations of the society, **Brownlee, 2011,** and **Yan,** and **Wu, 2011.** This information can be useful for the

generations to guide their problem solving activities, at the same time being dynamically modified by new information gathered by each new generation. The CA is modeled using two separate information spaces:

- Population Space.
- Belief Space.

The population space contains the set of possible solutions to the problem available in the present generation and evaluates with a performance function. The belief space models represent the actual cultural aspects. It stores information related to the problem solution that it has been found till the present generation and in turn influences to the evolution of the population space in subsequent generations thus the belief space is composed of a few knowledge sources, normative knowledge and situational knowledge. Communication between the two spaces is handled by a protocol consisting of two functions:

- An acceptance function, which selects the set of individuals that will influence the belief space.
- An influence function, which influences the creation of the next generation.

In addition the belief space requires an update function which is basically responsible for updating the belief space when it is required. The structure diagram of the communication protocol in the cultural algorithm is shown in **Fig. 2**.

The search engine will be used as a pre-search engine to feed the population space in the aggregation knowledge engine with a selected number of the best solution in order to speed up the process of finding and tuning the optimal PID control parameters and reducing the over all number of function evaluation.

In the proposed work, the search engine is based on particle swarm optimization (PSO) as fast and simple technique algorithm. PSO algorithms use a population of individuals (called particles) “flies” over the solution space in searching for the optimal solution**, Fang, et al., 2011,** and **Chiou, et al., 2012**. The particles were mainly utilized to determine three PID controller parameters *kp, ki* and *kd* as a particle *K* by $K=[kp,ki,kd]$ with its dimension being $\mathrm{POP}_{\mathrm{pre}}\times 3$.

where pop_{pre} is the number of pre-search particles.

The search engine will be fed continuously at each time instant by the breeding engine which is used to generate continuous random solutions with two conditions.

The first condition is that all random solutions should be lie within the practical experience values, as follows:

$$\left.\begin{aligned} kp_{\min} &\le kp \le kp_{\max} \\ ki_{\min} &\le ki \le ki_{\max} \\ kd_{\min} &\le kd \le kd_{\max} \end{aligned}\right\} \tag{10}$$

The second condition is that all random solutions should be submitted to Routh-Hurwitz criterion to check the closed-loop system stability. Mean Square Error (MSE) function for heating system is chosen as criterion for estimating the model performance to be minimized, as Eq. (11):

$$MSE=\frac{1}{pop}\sum_{k=1}^{pop}(T^{(k)}_{desired}-T^{(k)}_{output})^2 \tag{11}$$

where
pop is number of particles.
$T^{(k)}_{desired}$ is the desired temperature at *k* iteration.
$T^{(k)}_{output}$ is the output temperature at *k* iteration.
In pre-search, each particle has its own position [*kp*, *ki* and *kd*] and velocity [$\Delta kp, \Delta ki$ and Δkd] to move around the search space.
The previous best value of the particle is called as *pbest*. Thus, *pbest* is related only to a particular particle. It also has another value called *gbest*, which is the best value of all the particles *pbest* in the swarm.
Particles are updated afterwards according to Eqs. (12, 13, 14, 15, 16 and 17):

$$\Delta Kp_m^{k+1} = \Delta Kp_m^k + c_1 r_1 (pbest_m^k - Kp_m^k) + c_2 r_2 (gbest^k - Kp_m^k) \quad (12)$$

$$Kp_m^{k+1} = Kp_m^k + \Delta Kp_m^{k+1} \quad (13)$$

$$\Delta Ki_m^{k+1} = \Delta Ki_m^k + c_1 r_1 (pbest_m^k - Ki_m^k) + c_2 r_2 (gbest^k - Ki_m^k) \quad (14)$$

$$Ki_m^{k+1} = Ki_m^k + \Delta Ki_m^{k+1} \quad (15)$$

$$\Delta Kd_m^{k+1} = \Delta Kd_m^k + c_1 r_1 (pbest_m^k - Kd_m^k) + c_2 r_2 (gbest^k - Kd_m^k) \quad (16)$$

$$Kd_m^{k+1} = Kd_m^k + \Delta Kd_m^{k+1} \quad (17)$$

$m = 1,2,3,.....pop_{pre}$
where
K_m^k is the weight of particle *m* at *k* iteration.
c_1 and c_2 are the acceleration constants with positive values equal to 2.
r_1 and r_2 are random numbers between 0 and 1.
$pbest_m$ is best previous weight of m[th] particle.
$gbest$ is best particle among all the particle in the population.

It is proposed that 25% from the *pbest* particles of the pre-search engine individuals will be travelled to the aggregation knowledge engine in order to have a cognitive particles re-generation. The cognitive particles are evaluated by using a performance function to see how close they are to the optimal solution. In order to find the optimal set of the PID controller parameters, it needs to update the cognitive particle K_c = [kp_c, ki_c, kd_c] by using the two levels of CA communication through the acceptance function and the influence function. The acceptance function determines which cognitive particles from the current population are selected to impact the belief space. In this work, it is proposed that the acceptance function selects 20% from the cognitive particles depending on a good step response with minimum settling time (t_s), rise time (t_r) and MSE as a performance index in time domain.

Belief space is composed of normative knowledge and situational knowledge components. The normative knowledge component is composed of the upper and lower bounds of (t_s, t_r and MSE) of the variables cognitive particles accepted. The situational knowledge is a set of the elite kp_c, ki_c and kd_c.

Δkp_c, Δki_c and Δkd_c in the cognitive PSO algorithm are influenced by belief space. The direction of changing (‘velocity’) is determined by the difference between situational knowledge (kp_c)s, (ki_c)s and (kd_c)s in belief space and the checked values of the resolution parameters, as Eq. (18).

$$\left.\begin{aligned} \Delta kp_{c\min} \le \Delta kp_c \le \Delta kp_{c\max} \\ \Delta ki_{c\min} \le \Delta ki_c \le \Delta ki_{c\max} \\ \Delta kd_{c\min} \le \Delta kd_c \le \Delta kd_{c\max} \end{aligned}\right\} \tag{18}$$

If Δkp_c, Δki_c and Δkd_c are too high, cognitive particles might fly past good solutions. If Δkp_c, Δki_c and Δkd_c are too low, cognitive particles may not explore sufficiently beyond local solution. The influence function will lead the evolutionary process for the next generation through the normative knowledge vector that consists of:

- Δkp_c, Δki_c and Δkd_c.
- Cognitive acceleration values c_{c1},c_{c2}.
- Random number function r_{c1},r_{c2} between 0 to 1.
- Inertia weight factor for the velocity Ω_c

In order to update the cognitive particles velocity, Eqs. (19, 20, and 21) are used in the next iteration.

$$\Delta Kp_{cn}^{k_c+1} = \Omega_c(\Delta Kp_{cn}^{k_c}) + c_{c1}r_{c1}(pbest_{cn}^{k_c} - Kp_{cn}^{k_c}) + c_{c2}r_{c2}(gbest_c^{k_c} - Kp_{cn}^{k_c}) \tag{19}$$

$$\Delta Ki_{cn}^{k_c+1} = \Omega_c(\Delta Ki_{cn}^{k_c}) + c_{c1}r_{c1}(pbest_{cn}^{k_c} - Ki_{cn}^{k_c}) + c_{c2}r_{c2}(gbest_c^{k_c} - Ki_{cn}^{k_c}) \tag{20}$$

$$\Delta Kd_{cn}^{k_c+1} = \Omega_c(\Delta Kd_{cn}^{k_c}) + c_{c1}r_{c1}(pbest_{cn}^{k_c} - Kd_{cn}^{k_c}) + c_{c2}r_{c2}(gbest_c^{k_c} - Kd_{cn}^{k_c}) \tag{21}$$

The Eqs. (22, 23 and 24) for updating and next generation of cognitive particles, as follows:

$$Kp_{cn}^{k_c+1} = Kp_{cn}^{k_c} + \Delta Kp_{cn}^{k_c+1} \tag{22}$$

$$Ki_{cn}^{k_c+1} = Ki_{cn}^{k_c} + \Delta Ki_{cn}^{k_c+1} \tag{23}$$

$$Kd_{cn}^{k_c+1} = Kd_{cn}^{k_c} + \Delta Kd_{cn}^{k_c+1} \tag{24}$$

$n = 1,2,3,.....pop_c$

where

pop_c is number of cognitive search of cognitive particles.

$K_{cn}^{k_c}$ is the weight of cognitive particle n at k_c iteration.

$pbest_{cn}$ is best previous weight of n^{th} cognitive particle.

$gbest_c$ is best cognitive particle among all the cognitive particles in the population space.

After updating and generating new cognitive particles of the PID parameters in the population space for the next iteration by using Eqs. (19, 20, 21, 22, 23 and 24), two conditions should be applied; the first condition is checking of the range acceptance of robust PID controller parameters as Eq. (10) for achieving the stability and second condition is applying Eq. (11) in order to estimate the value of the cost function for each particle, if one or two conditions are not true, this mean Δkp_c, Δki_c or Δkd_c violated the normative knowledge and it is forced back into the cognitive search space dictated by the normative knowledge. Else, at the end of each best cognitive particle generation, the normative knowledge is updated with the bounds of the accepted particles and the situational knowledge component is updated if necessary. Then continue the proposed algorithm until finding the optimal values of the robust PID controller parameters.

4. SIMULATION RESULTS

This section discusses the mapping between the real heating system and the numerical simulation by using Matlab package. The signal of the proposed robust PID controller will feed the heater unit of the heating system and this signal has to be within range (0 to 1500)watt because of the specification of real heater actuator ,therefore; will need a linear relationship with saturation transfer function (0-1500) in order to satisfy gain mapping and to limit the heater actuator output for the real heating system modeling.

To show the dynamic behavior of the heating system, the open loop step response of the temperature for the heating system is shown in **Fig. 3**, when applying a 21.49watt as input step change in the heater actuator of system in order to increase the heating system temperature by $1C^o$ with reference to its temperature at the initial condition which is equal to $25C^o$. The settling time for the temperature response of the heating system is equal to 39.83 minute and rise time is equal to 22.33 minute and the time constant is equal to 10.2 hour. The sampling interval for the heating system is chosen to be 1 minute using Shannon theorem.

The proposed robust PID controller scheme, as in **Fig. 1**, is applied to the heating system model and it used cognitive methodology for auto-tuning the parameters of the PID controller on-line to find the best temperature response for the heating system.

The proposed cognitive methodology is set to the following parameters:

Population of pre-search is equal to 100.

Population of cognitive search is equal to 25.

Population of belief space is equal to 5.

Situational knowledge is equal to 5×3.

Normative knowledge is equal to 1×8.

Number of weights in each particle is equal to 3 because there are three parameters for PID controller.

Number of pre-search iteration (k) is equal to 10.

Number of cognitive iteration (k_c) is equal to 20.

Figs. 4a, 4b and **4c** represent the simulation results of the closed loop time response of the temperature control system with on-line auto-tuning robust PID controller based on cognitive methodology with initial temperature $25C^o$ and with proposed external disturbance function as Eq.

(25) which has been added in order to investigate the robustness and adaptation of the PID controller and to evaluate the performance rejection of the heal loss and model uncertainties.

$$d(t) = 10\sin(10kt) \tag{25}$$

Fig. 4a shows the response of the output temperature of the heating system to a step change, it had no over shoot and the steady-state error was approached to zero value in each step when the desired steps change in temperature were (50, 60 and 70) C^o and the external disturbance effect was very small during sixty samples.

The robust PID control action response is shown in **Fig. 4b** that it had few spikes in response to the desired step change in temperature with very small oscillation in order to keep the temperature output of the heating system within desired range and minimize tracking temperature error of the system and reduce the disturbance effect on the heating system.

Fig. 4c shows the error between the desired temperature and the temperature output of the heating system. The error was small value in the transient at each step change and became much close to zero in steady state with very small oscillation. The optimal parameters kp_c, ki_c and kd_c at each sample for the robust PID controller that have been tuned on-line based on cognitive methodology are shown in **Figs. 5a, 5b** and **5c** respectively.

Fig. 6 shows the optimal “velocity” Δkp_c, Δki_c and Δkd_c at each sample that have been calculated in the belief space in order to influence the particles kp_c, ki_c and kd_c of the next generation.

5. HARDWARE DESIGN AND REAL-TIME RESULTS

In this section, the experimental setup for the real-time heating system temperature control is shown in **Fig. 7**.

The setup of heating system consists of:

- The water tank that has volume (30, 25, 30) cm.
- AC heater actuator that has heat energy range (0-1500) watt.
- Temperature sensor LM134 with operation range (0 to 100) C^o.
- Data acquisition device from National Instrument NI Company type 6009USB with guided LabVIEW package.
- Digital phase controller based AT89C51 micro-controller to control power magnitude.
- AC drive circuit based Triac device.
- Electronic circuit board for signal conditioning based operational amplifier TL064.
- DC power supply that provides power to the circuitry.
- Laptop computer type Pentium dual-core 1.73GHz is used for the real time computation.

In the real-time computer control system based on LabVIEW package, the cognitive methodology has been applied to find optimal parameters for robust PID controller that controlled the temperature of the heating system in the real-time with sampling time equal to 1 minute. The front panel diagram of the control algorithm has been written in the LabVIEW, as shown in **Fig. 8**.

Fig. 9 shows the electronic circuit diagram design for the temperature control system and it consists of multi-stage as follows: the first stage is signal conditioning circuit which includes a voltage follower with unity gain to avoid the attenuation in the feedback signal of the temperature sensor LM134 and the first order low pass filter stage that has a cutoff frequency of 10Hz which will remove possible noise components that occur in the sensor outputs especially within main supply frequency at 50Hz. This filter is built using TL064 quad operational amplifier, **Faulkenberry, 1986**.

The output of this amplifier is fed to the gain amplifier stage that amplified the sensor signal by five times in order to make the sensitivity of this sensor equal to $50mV/C^o$ instead of $10mV/C^o$ that make the full range of operation (0 to 5) volt then its fed to the analog to digital converter ADC 14 bit high speed low power successive approximation converter of the NI-DAQmx-USB 6009 device with range of input voltage (0 to 5) volt as a second stage.
Inside the personal computer, LabVIEW software instructions compares the sensed temperature signal received via this interface with the set-point desired temperature. The resulting error is given as an input to the robust PID controller and found the optimal parameters of the PID controller by using cognitive control methodology that has been built in the LabVIEW package.
The optimal digital control action generated from the robust PID controller will be sent to the digital phase controller which operates as a phase and magnitude detector for the Alternative Current (AC) by using micro-controller AT89C51, as third stage.
The digital data of control action is sent to the NI-DAQmx-USB 6009 device though the USB connector then the digital data will be sent as eight bits within range (00 - FF)hex to the port two (P2.x) of digital phase controller in order to analyze this data by using the assembly program of AT89C51**, Scott Mackenzie, 1999,** which convert the digital data action (00 - FF)hex to generate the firing angle pulse on the gate of the Traic device BT136 through isolator pulse transformer to control the AC power of the heater actuator (0 – 1500) watt. Assume the AC frequency is equal to 50Hz, the firing angle pulse has range from (0 – 20) msec.
The isolator circuit interface has been used between the DAQ (Data Acquisition) card and the heater actuator to prevent the possibility of any back-flow of AC current to the DAQ card from Triac device controller of heater actuator.
The phase detector control action program has been written in assembly language of AT89C51 microcontroller, as shown below:

```
ORG 000h
         SJMP START
ORG 003H
         MOV IE,#00H
         MOV R0,P2
         CLR TF0
         CLR TR0
Count:   MOV TL0,#0DCH
         MOV TH0,#0FFH
         SETB TR0
Cheak1:    JNB TF0,Cheak1
         CLR TR0
         CLR TF0
         DJNZ R0,Count
         SETB P1.0
         MOV TL0,#18H
         MOV TH0,#0FCH
         SETB TR0
Cheak2: JNB TF0,Cheak2
         CLR TR0
         CLR TF0
         CLR P1.0
         MOV IE,#81H
         RETI
START:    CLR P1.0
```

```
        CLR TF0
        CLR TR0
        MOV TMOD,#01H
        MOV IE,#81H
        MOV IP,#01H
        SETB IT0
Cheak3: SJMP Cheak3
END
```

The temperature response for the heating system in real-time was estimated within one hour, as shown in **Fig.10a**. It can be seen that response has three steps change in the desired temperature (50, 60 and 70) C^o and at steady state, the response has small fluctuation due to convection current of heat transfer in water of the heating tank.

The tracking error between the desired temperature and the actual temperature output of the heating system is shown in **Fig. 10b**. The firing angle signal of the AC heater driver circuit is shown in **Fig. 10c**.

The response of the feedback robust PID control action is shown in **Fig. 10d**. It has spike during the step change in the desired temperature as well as a small oscillation can also be observed. This action of the controller has kept the temperature of the heating system within the desired value with minimum tracking temperature error and it has attempted to reduce the disturbance effect on the heating system.

In fact, there are small differences in results between the numerical simulation and real-time control system because in the real-time state there were accumulation errors such as undesirable characteristics of temperature sensor "non-linearity, drift, and offset", offset in the operational amplifier output, and the quantization error of the analog to digital converter; therefore, the results in the real-time had small fluctuation in the actual temperature output of the heating system.

6. CONCLUSIONS

A robust cognitive PID temperature control methodology for the heating system model has been designed and tested using Matlab package and carried out in real-time using LabVIEW package on the real heating system model.

Simulation and real-time computer control results show evidently that the proposed robust PID controller model has demonstrated effectively the capability of tracking desired temperature as well as evaluating the performance rejection of the heat loss disturbance and uncertain parameter of the real system, especially with regards to the external disturbance effect.

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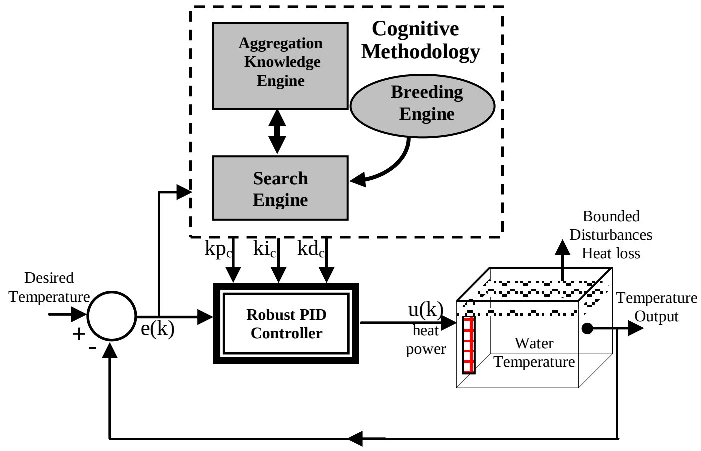

Figure 1. The proposed block diagram of the robust PID controller for heating system.

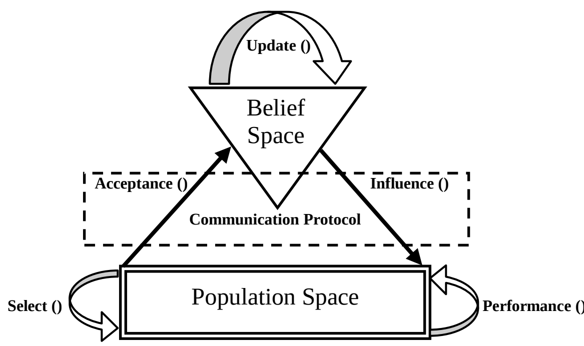

Figure 2. The structure diagram of the communication protocol.

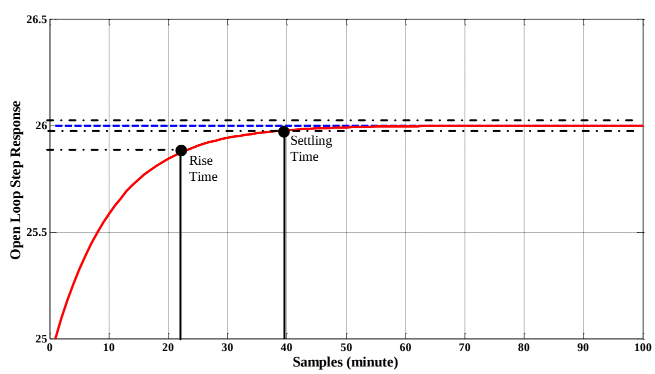

Figure 3. Step response of open loop heating system.

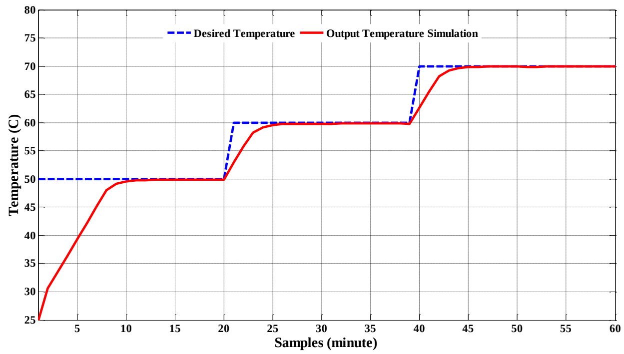

Figure 4a. Heating system output temperature simulation.

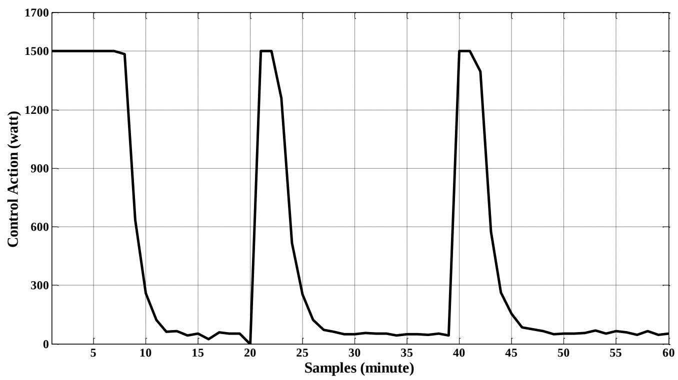

Figure 4b. Control action simulation.

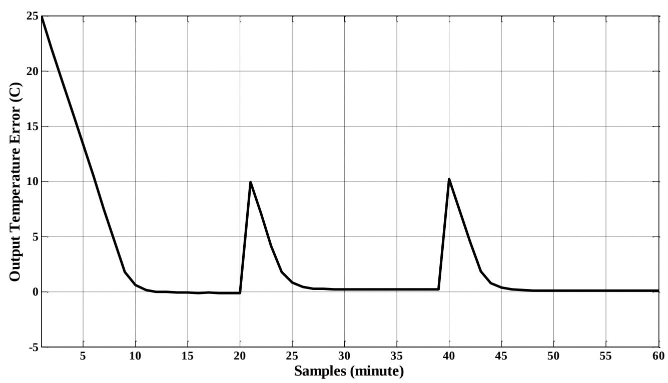

Figure 4c. Output temperature error simulation.

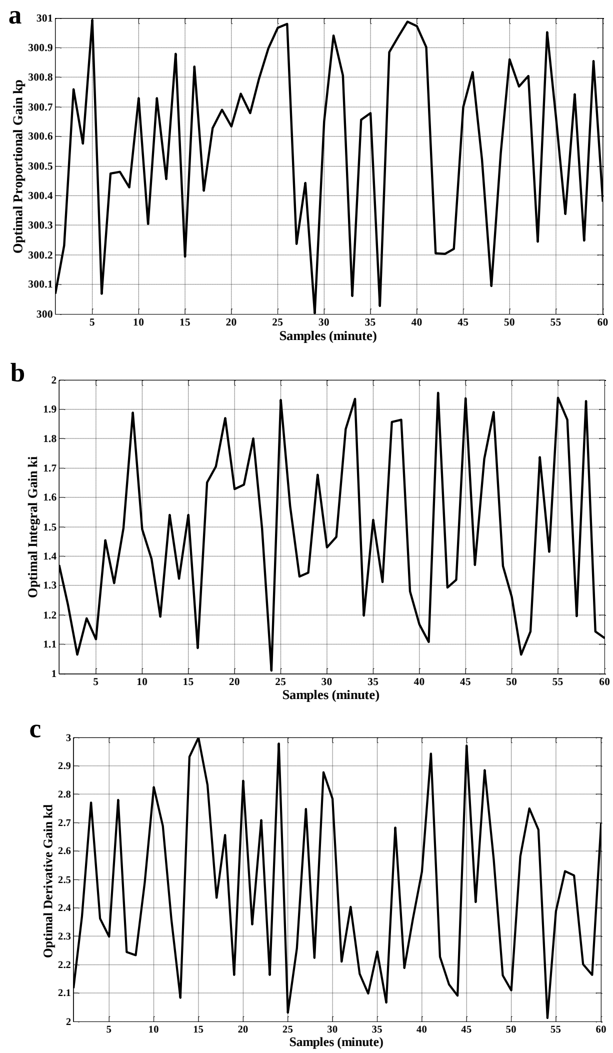

Figure 5. Optimal parameters of robust PID controller: a) Proportional gain; b) Integral gain; c) Derivative gain.

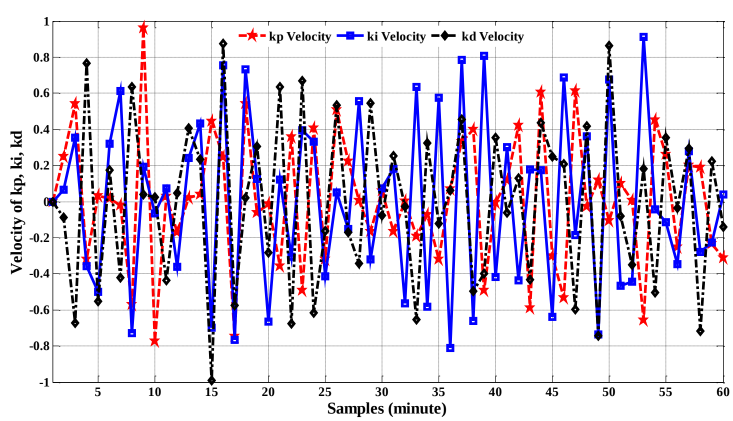

Figure 6. Simulation of the best gains velocity.

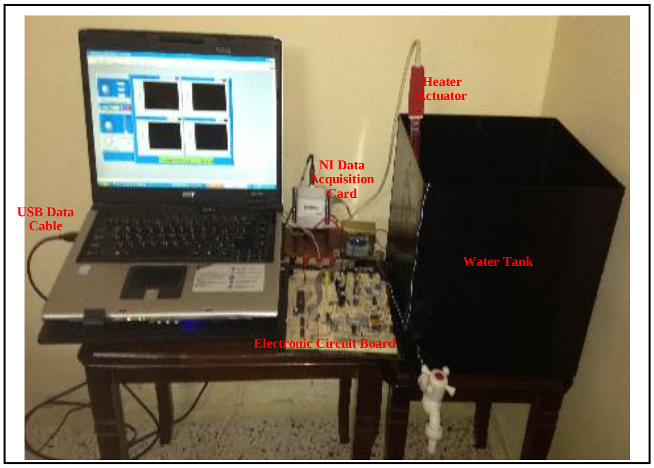

Figure 7. The experimental work in the real-time temperature control system.

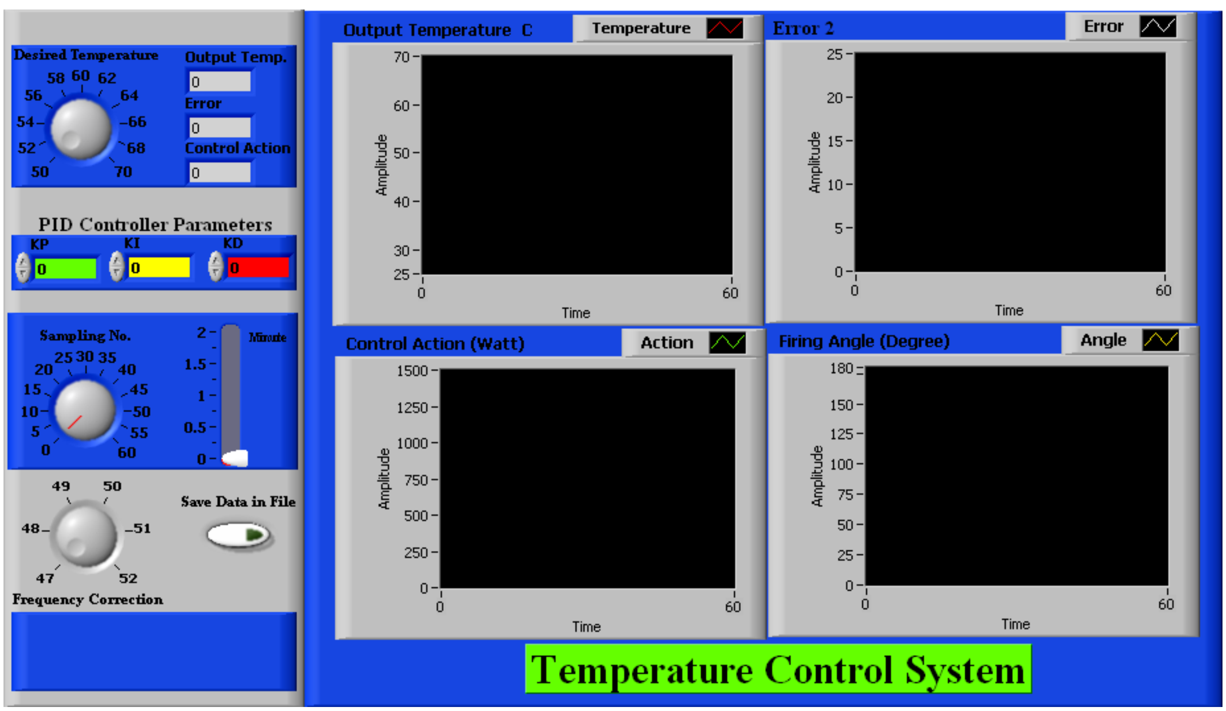

Figure 8. Front panel diagram for control algorithm.

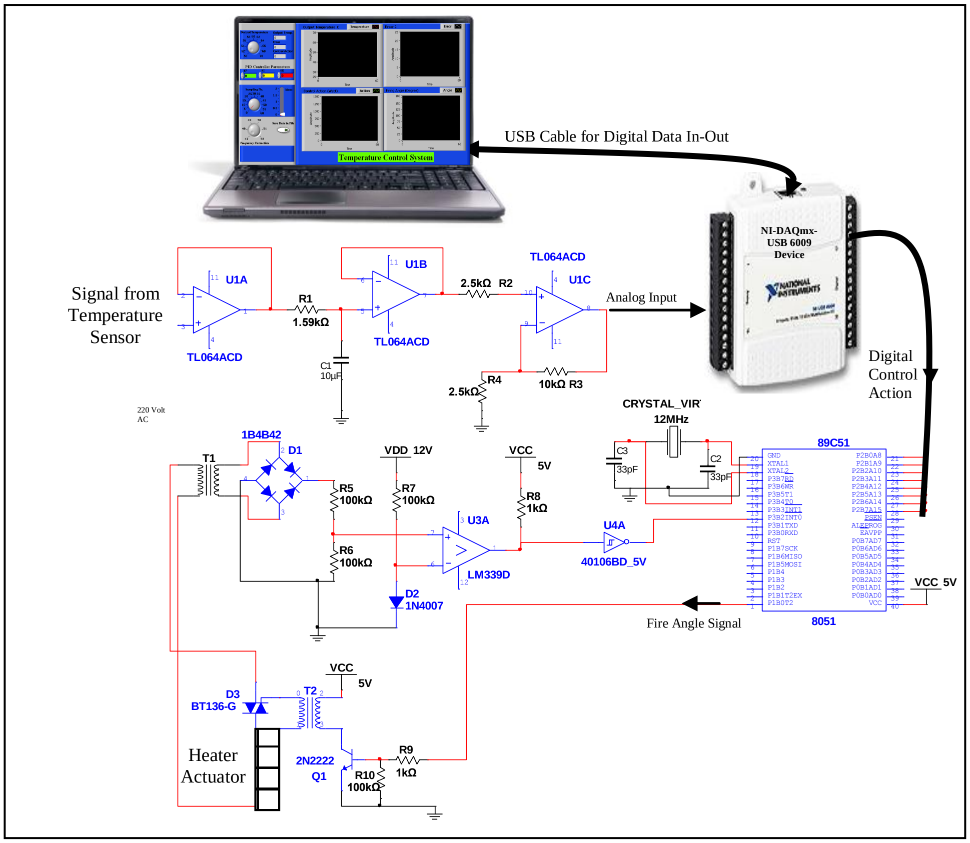

Figure 9. The schematic diagram of the electronic control circuit.

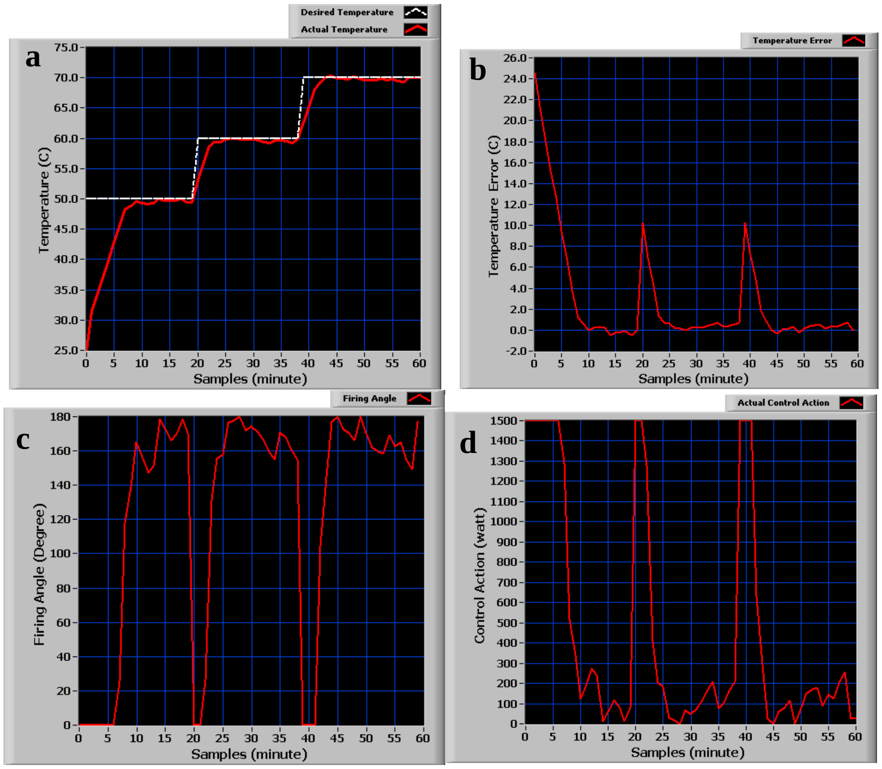

Figure 10. (a) Actual temperature output for heating system; (b) Temperature error; (c) Actual firing angle; (d) Actual control action.

Table 1. Heating system real parameters.

Real parameter	**Values**
A: surface area of the tank	0.075 m^2
h: over heat transfer coefficient	11 $watt/m^2C^o$
M: mass of water in tank	7.5 kg
cp: specific heat of water	4.2 KJ/kgC^o